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14. ABSTRACT
Report developed under SBIR contract for topic A99-092. This report describes the design and development of a vehicle Corrosion Expert System (CES). CES has immediate utility in the automotive industry by vehicle manufactures that have the requirement for an accurate predictive tool which could eliminate or reduce the expensive Accelerated Corrosion Testing phase of the new vehicle development effort. The Vehicle Corrosion Expert System supports four modules representing different points of the vehicle's life cycle. 1) In **Preliminary Design** of new vehicles as a tool for performing design tradeoff studies and in giving general guidance to the new vehicle designer. 2) In **Detailed Design** for continual certification of the new design and in computer simulation of Accelerated Corrosion Testing of new vehicle designs. 3) In **Vehicle Fleet Operations** for forecasting the maintenance requirements of the existing fleet. And 4) In **Logistic Management** by top-level decision makers conducting "What-if" analysis to determine the projected life cycle cost, fleet readiness and cost of corrosion for the fleet under different operational scenarios. Each of these modes offers a different capability and level of detail required to allow the user to use the Expert System for his area of interest.

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1.0 Results of the Phase I Work

This SBIR topic is to develop an Expert System to predict the corrosion and deterioration of vehicles. This topic is significant to the US Army because recent studies have shown that 25% of all maintenance recalls are due to corrosion. The proposed Expert System will allow the corrosion or maintenance engineer to anticipate the vehicle's deterioration and thereby significantly reduce the number of incidents where corrosion forces a vehicle recall. In addition, the Expert System will allow the Army to be more intelligent buyers of vehicles and components.

Having an accurate and reliable prediction and forecasting capability would allow the cognizant corrosion engineering staff within TACOM to identify design, operational and maintenance problems early in a vehicle's introduction. Decisions could also be made early in the design stage of new vehicle products as to how changes in materials, design and manufacturing plans & processes might affect the service life of the vehicle and their major components, resulting in significant savings in both time and money. Once a reliable computer simulation tool has been proven, existing physical testing of the vehicle could be reduced saving over $1M and cutting up to 24 months time out of the new vehicle introduction schedule

In Phase I, a preliminary design of the Expert System software was performed. The effort was divided into seven tasks:

1. Selecting an Expert System Inference Engine
2. Interface with Vehicle Corrosion and Maintenance Databases
3. Interface with Vehicle Mounted Corrosion Sensor Data
4. Identification of needed Autonomous Agents
5. Establishing an Expert Knowledge Base
6. Formulation of the Corrosion Forecasting Model, and
7. Development of a Proof-of-Concept Software Demonstration.

In the first task Jess (Java Expert System Shell) was selected as the development environment. Jess is a rule-based inference engine that uses the Rete algorithm (Forgy82) for processing the forward and backward chaining of difficult many-to-many matching problems. Jess provides the ability to manipulate and directly reason about Java objects. It is also a powerful scripting environment from which you can create Java objects and call Java methods without compiling any Java code. Java is a "cutting edge" language developed by Sun Microsystems to provide an extremely high level of portability of software between different computers and operating systems. Today Java programs will run on PC's under Windows 95/98/2000/NT, Unix/Linux, and Macintosh computers. For this reason Java has become ***THE*** language of the Internet. Nearly all sophisticated Internet software is written in Java.

In task 2, the various data sources for the expert knowledge were identified. They include:

- "Lesson Learned" from SAE, TACOM and Manufacturers,
- SDC (Statistical Data Collection),
- FVPOS (Field Vehicle Performance Data Systems),

- Accelerated Corrosion Test data,
- Vehicle mounted corrosion sensor data,
- Old MTL (ARC) databases and others from Federal Labs,
- NACE databases,
- 21st Century Trucks,
- Vendor/manufacturer databases, including:
    1. Vehicle design data,
    2. Warranty data,
    3. Measurement of micro-environment, and
    4. Vehicle test data from vendor's proving grounds.

In Task 3, three the appropriate interfaces were established for the infusion of data collected from vehicle-mounted sensors, including those proposed by the contractor, Material Modification Inc. (MMI), for the companion Phase I effort on "Sensor Technology and Monitoring Corrosion of Land-based Vehicles." The effort included specifying the digital time series needed from such on-board instrumentation, including:

- The mean value of measurement converted and scaled to meaningful engineering units,
- The standard deviation from the mean value determined from samples collected over the time period of the data sample set. (Note: If only one data point is used for the mean value then the standard deviation should be an estimate of the data precision. The data precision can be determined from the root-mean-sum of the squares of the estimated precision's of the various components in the data collection system, e.g. sensor, amplifier, A to D, etc., and the precision variations in the environment and other influencing variables.)
- The number of data samples used in the calculation of the mean and standard deviation,
- The period of time over which the data set was recorded to produce the mean and standard deviation values,
- The time base for the data set,
- The serial number or other identifying values to determine which vehicle was used for the data collection,
- A geometric location or spatial location of the sensor on the vehicle, and
- Any other supporting data (e.g. temperature, humidity, etc.).

In task4, the structural components of the expert system were analyzed and autonomous "agents" were identified for incorporation into the model. Three uses for the agents are:

- Agents tied to the rule base inference engine for processing the rules,
- Agents in the system Explanation Facility which play back the reasoning for a decision to the reader,

- Agents in the knowledge acquisition facility to assist the human expert in building the knowledge.

The general definition of an autonomous agent is a system situated within a part of an environment and acts on it overtime, in pursuit of its own agenda and so as to effect what it senses in the future. In the context of corrosion expert system the agents are task-specific, software computational autonomous agents.

In Task 5, the mechanisms for corrosion and deterioration were identified for incorporation into the Expert System's Knowledge Base. They include:

- Uniform Corrosion which occurs when the metal surface, upon exposure to the atmosphere or an electrolyte, forms minute anodic and cathodic regions which shift about as corrosion progresses.
- "Galvanic" Corrosion of one metal is brought about (or accelerated) by electric contact with a different metal which acts as a cathode when both metals are subjected to an electrolyte. Sometimes Galvanic Corrosion is deliberately induced to forestall corrosion of a cathode metal, for example when Zinc coatings are applied to steel.
- Pitting where small areas corrode preferentially, forming cavities (pits) in the metal surface. This occurs when metals that form passive oxide layers, such as stainless steels, are exposed to environments containing certain ions, notably chloride. The corrosive ions penetrate weak points in the normally protective oxide layer, creating localized corrosion cells. The localized corrosion site, or pit, is the anode, while surrounding non-corroded metal is the cathode.
- Crevice Corrosion, which occurs in locations such as joints or recesses, is normally caused by differential aeration. That is, the metal within the crevice is subjected to less oxygen than the surrounding metal. The greater availability of oxygen outside the crevice sets up an electrochemical cell, with the crevice as the anode. Once the dissolution begins, the corrosion process becomes autocatalytic (as in pitting); resulting in intense localized corrosion.
- Poultice Corrosion occurs when deposits of mud or other debris hold stagnant moisture in contact with the metal surface. As with crevices, differential aeration sets up an electrochemical cell that initiates corrosion in oxygen-starved locations. In addition, such deposits absorb moisture from the atmosphere. They also tend to prolong the presence of moisture which would otherwise drain away or evaporate, adding to the increased corrosion difficulties.
- Stress Corrosion Cracking (SCC) can happen when a metal or alloy, susceptible to a given corrosive agent, is exposed to that substance while simultaneously under tensile stress. SSC effects a number of alloys including stainless steels, and alloys of aluminum, magnesium and titanium. A related phenomenon, hydrogen embrittlement, is a problem with high strength steels. Plastics can also suffer stress-corrosion cracking and some polycarbonates will "craze", or develop a pattern of surface cracks, when exposed to certain chemicals.
- Intergranular Corrosion is a preferential attack along grain boundaries, arising from electrochemical potential differences between grains and grain boundary precipitates.

Intergranular corrosion is a problem with austenitic stainless steels subject to improper heat treatment, unintentionally during welding. Chromium carbide precipitates form at grain boundaries, leaving adjacent grains depleted in chromium and hence vulnerable to corrosion.

- Exfoliation, or layer corrosion, is a problem with high strength aluminum alloys. It occurs when a vulnerable alloy is rolled so as to form an elongated grain structure. Upon exposure to an electrolyte, corrosive attack proceeds along subsurface paths parallel to the surface. The corrosion products occupy a larger volume than the alloy itself, and therefore delaminate layers of uncorroded metal.
- De-alloying or Parting Corrosion, occurs in certain alloys when a corrosive medium may selectively dissolve one or more alloying elements without dissolving the whole alloy, such as in the dezincification of brass and the leaching of cast iron.
- Fretting Corrosion occurs when two surfaces, at least one of which is metal, are in contact with relative movement between them, in the presence of a corrosive medium. The result is pitting or stress-corrosion induced cracks.
- Corrosive Fatigue is the accelerated failure of a part caused by repeated stress cycling in a corrosive environment.
- Impingement or Erosion Corrosion occurs when a corrosive fluid stream impinges on a metal surface, resulting in localized erosion, such as might occur in a heat exchanger.

In Phase I only the framework galvanic corrosion was modeled and demonstrated in the "Proof-of-Concept" demo software.

In Phase II galvanic corrosion will be pursued as the principal area of concern. The expert knowledge needed to recognize the various forms of corrosion and to prescribe the appropriate design and/or maintenance actions required will be formulated. In addition, the influence of uniform, crevice and poultice corrosion will be modeled and the interaction and combination with galvanic corrosion will be investigated and included in the system.

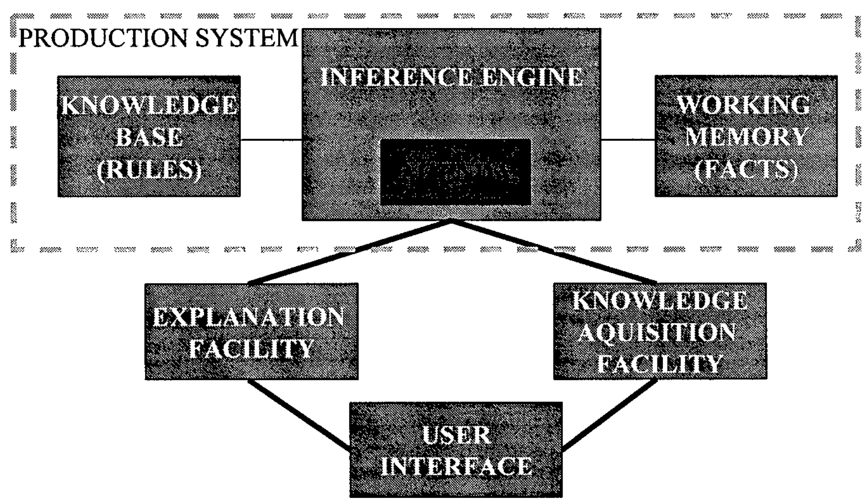
The other forms of corrosions listed above are of lesser importance in modern automotive design and therefore will be delegated to a study task in Phase II. In addition because of their importance to current and future vehicle systems, the deterioration of rubbers, plastics and composite materials will be studied in Phase II as well for future incorporation into the expert system.

In task 6 the architecture shown in Figure 1 was formulated for CES, (Corrosion Expert System). It is composed of four parts:

1. **User Interface** by which the user and the expert system communicate. A Java-based Graphical User Interface (GUI) will be used.
2. **Explanation Facility** for the expert system to explain its reasoning to the user.
3. **Knowledge Acquisition Facility** for automatically entering new knowledge into the system in the future.
4. A **Production System** composed of:

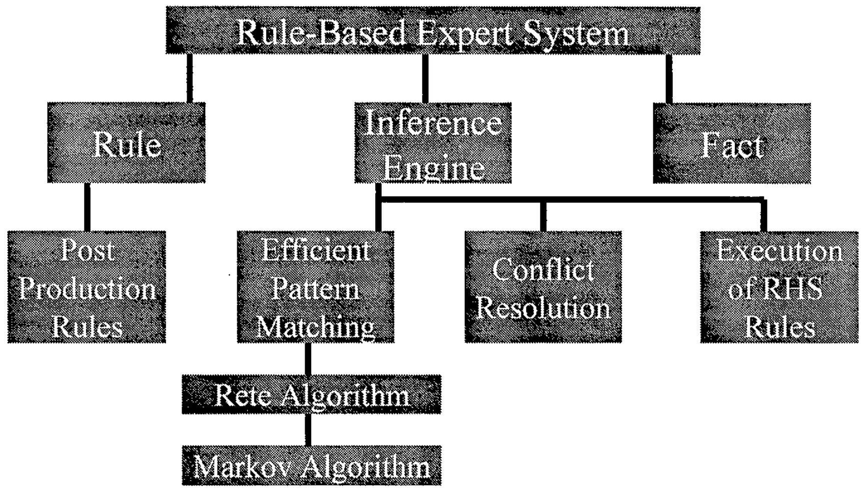
- A long-term memory containing a knowledge base of rules formulated with the help of human experts through the Knowledge Acquisition Facility,
- Working memory containing a global database of facts used by the rules,
- Inference engine that decides which rules are satisfied by the facts or objects, prioritizes the satisfied rules and executes the rules with the highest priority, and
- Agenda containing a prioritized list of rules created by the inference engine, whose patterns are satisfied by facts or objects in working memory.

Figure 1: Rule-Based Expert System



A more detailed view of the production system is shown in Figure 2. Facts are compared against rules using an efficient pattern matching system containing both Rete and Markov algorithms. Any conflicts are resolved and single action is executed as the right hand side of the rules. This is iterated until the expert system arrives at a conclusion.

Figure 2: Production System Details



In Task 7 a simple proof-of-concept prototype demonstrating the ability to the system to forecast galvanic corrosion was conducted. The Ford F150 transmission bell housing was chosen as the specific parts to analyze. This part is made of magnesium and is fastened together using nylon coated stainless steel bolts. Since magnesium is anodic (or sacrificial) to all other engineering metals, is has a very high propensity for galvanic corrosion. The nylon coating on the bolts prevent this from happening with the new vehicle. But what if when the vehicle is in service the coating becomes scratched? Or worse yet, what if uncoated ones replace these bolts? The corrosion potential is very high and it is a great concern not only to Ford for the F150 but to the automotive industry for the general use of magnesium in vehicles. The demo allows the user to select the bolt section and the galvanic corrosion evaluation begins assuming magnesium housing and uncoated stainless steel bolts. Alternatively, the user can insert any materials for the two items. The hierarchical rule logic applied in this demo is shown as Appendix A.

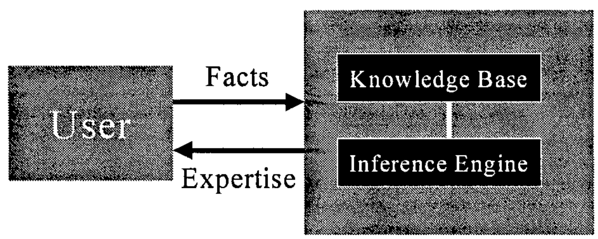
One could argue that the hierarchical logic found in Appendix A could have been programmed using conventional nested "if-then-else" or "case" statements and therefore an expert system is not really necessary. Although for this crude demo this is true, the result would have been highly inefficient, slow and would have required perhaps ten times as many lines of code to have encoded the logic using nested "if" or "case" statements. Another advantage indirectly related to speed is the ability of saving the state of facts and rules in an expert system and then retrieving this state when reentering the expert system at a later date. With a convention language the entire analysis must be rerun. Finally in Phase II, when more complex predicate logic and uncertainty analysis using fuzzy logic is employed, only an expert system will be capable of doing the job.

2.0 Background

2.1 Introduction

An expert system is a computer system that emulates the decision-making ability of a human expert. The term "emulate" means that the expert system is intended to act in all respects like a human expert not just a simulation of some areas. The user supplies facts or other information to the expert system and receives expert advice or expertise in response. Internally, the expert system consists of two main components: the *Knowledge Base* and the *Inference Engine*. The Knowledge Base contains the knowledge with which the inference engine draws conclusions. These conclusions are the expert system's responses to the user's queries for expertise (Figure3).

Figure 3: Expert System Function

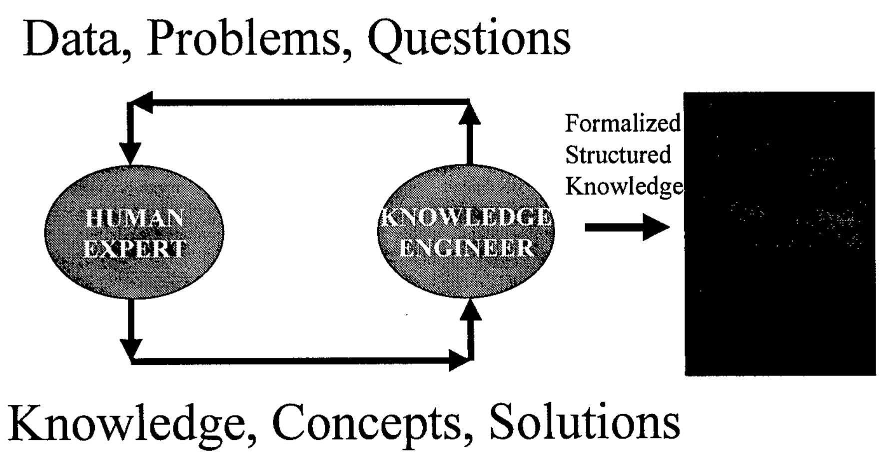


Useful knowledge-based systems have also been designed to act as an intelligent assistant to a human expert. These intelligent assistants are designed with expert systems technology because of the development advantages. As more knowledge is added to the intelligent assistant, it acts more like an expert. Thus, developing an intelligent assistant may be a useful milestone in producing a complete expert system. In addition, it may free up more of the expert's time by speeding up the solution of problems.

2.2 Knowledge Acquisition

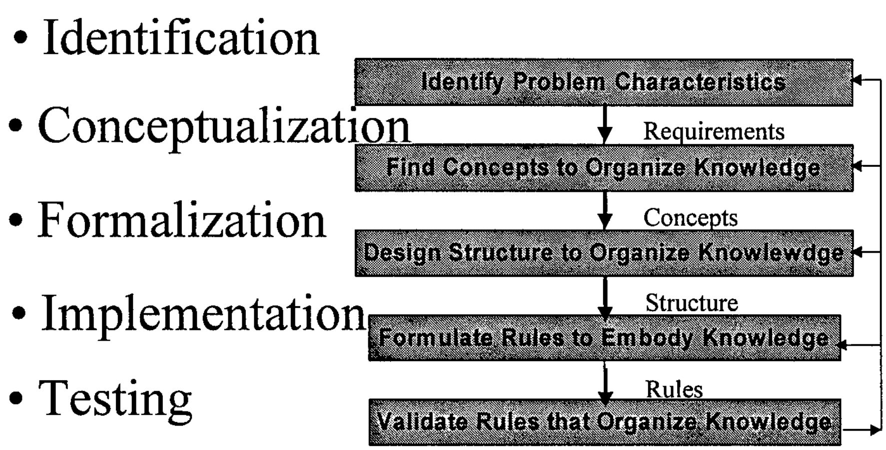
Expert system embodies unwritten knowledge that must be extracted from an expert by extensive interviews with a knowledge engineer over a long period of time. The process of building an expert system is called ***knowledge engineering*** and is done by knowledge engineer. Knowledge engineering refers to the acquisition of knowledge from a human expert or other source and its coding in the expert system.

Figure 4. Knowledge Flow



The general stages in the development of an expert system are illustrated in Figure 4. The knowledge engineer first establishes a dialog with the human expert in order to elicit the expert's knowledge. This state is analogous to a system designer in conventional programming discussing the system requirements with a client for whom the program will be constructed. The knowledge engineer then codes the knowledge explicitly in the knowledge base. The expert then evaluates the expert system and gives a critique to the knowledge engineer. This process iterates until the system's performance is judged by the expert to be satisfactory and proceeds along the five steps shown in Figure 5.

Figure 5. Knowledge Representation



Expert systems are generally designed differently from conventional programs because the problems usually have no algorithmic solution and rely on inferences to achieve a reasonable solution. Note that a reasonable solution is about the best that we can expect if no algorithm is available to help us achieve the optimum solution. Because the expert system relies on inferences, it must be able to explain its reasoning so that its reasoning can be checked. This is accomplished with an Explanation Facility, which is an integral part of sophisticated expert systems. In fact, elaborate Explanation Facilities may be designed to allow the user to explore multiple lines of "what if" or hypothetical reasoning questions and even to translate natural language in rules.

Human experts also know the extent of their knowledge and qualify their advice as the problem reaches their limits of ignorance. A human expert also knows when to "break the rules." Unless expert systems are explicitly designed to deal with uncertainty, they will make recommendations with the same confidence even if the data they are dealing with are inaccurate or incomplete. An expert system's advice, like that of a human expert, should degrade gracefully at the boundaries of ignorance.

An example of the power of knowledge is the game of chess. Although computers now rival humans, people play well despite the fact that computers can do calculations millions of times faster. Studies have show (Chase73) that human expert chess players do not have superpowers of reasoning but instead rely on knowledge of chess piece patterns built up over years of play. One estimate places an expert chest player's knowledge at about 50,000 patterns. Humans are very good at recognizing patterns such as pieces on a chess board, as a computer might, the human analyzes the game in terms of patterns that reveal long-term threats while remaining alert for short-term surprise moves.

Although domain knowledge is powerful, it is generally limited to the domain. For example, a person who becomes an expert chess player does not automatically become an expert at solving math problems or even an expert at checkers. While some knowledge may carry over to another domain, such as the careful planning of moves, this is a skill rather than genuine expertise.

A practical limitation of many expert systems today is lack of causal knowledge. That is, the expert systems do not really have an understanding of the underlying causes and effects in a system. It is much easier to program expert systems with shallow knowledge based on empirical and heuristic knowledge than with deep knowledge based on the basic structures, functions, and behaviors of objects. Heuristic knowledge is not guaranteed to succeed in the same way that an algorithm is a guaranteed solution to a problem. Instead, heuristics are rules of thumb or empirical knowledge gained from experience that may aid in the solution but are not guaranteed to work. However, in many fields, such as medicine and engineering, heuristics play an essential role in some types of problem solving. Even if an exact solution is known, it may be impractical to use because of cost or time constraints. Heuristics can provide valuable shortcuts that can reduce both time and cost.

2.3 Explanation Facility

Expert systems must be able to justify its conclusions in the same way a human expert can explain why a certain conclusion was reached. This capability is provided by an Explanation Facility, which is used to provide an understandable check of the reasoning for humans. An Explanation Facility will allow the user to ask how the system came to a certain conclusion and why certain information is needed. The question of how the system came to a certain conclusion is easy to answer in a rule-based system because a history of the activated rules and contents of working memory can be maintained in a stack. In addition, the user can ask "What If"-type questions to explore alternate reasoning paths through hypothetical reasoning.

A second reason for having an Explanation Facility occurs in the development phase of an expert system to confirm that the knowledge has been correctly acquired and is being correctly used by the system. This is important in debugging because the knowledge may be incorrectly entered by typos or is incorrect due to misunderstandings between the knowledge engineer and the expert. A good Explanation Facility allows the expert and the knowledge engineer to verify the correctness of the knowledge. Also, because of the way typical expert systems are constructed, it is very difficult to read a significant program listing and understand its operation.

The Explanation Facility will list all the facts that made the latest rule execute. Additional optional features include:

- List all the reasons for and against a particular hypothesis. A hypothesis is a goal that is to be proved, such as "the part has crevice corrosion." There may be multiple hypotheses, just as a part may experience multiple forms of corrosion. A hypothesis can also be viewed as a fact whose truth is in doubt and must be proved.
- List all the hypotheses that may explain the observed evidence.

- Explain all the consequences of a hypothesis. For example, assuming that the part does have crevice corrosion, does the crevice show intense localized corrosion? If this symptom is observed, it adds credibility that the hypothesis is true. If the symptom is not observed, it reduces the credibility of the hypothesis.
- Give a prognosis or prediction of what will occur if the hypothesis is true.
- Justify the questions that the program asks of the user for further information. These questions may be used to direct the line of reasoning to likely diagnostic paths. In most real problems it is too expensive to take too long to explore all possibilities and some way must be provided to guide the search for the correct solution. For example, consider the cost, time, and effect of administering all tests to part displaying corrosion just to determine the form of corrosion.
- Justify the knowledge of the program. For example, if the program claims that the hypothesis "the part has crevice corrosion" is true, the user could ask for an explanation. The program might justify this conclusion on the basis of a rule that says that if the crevice has intense localized corrosion then the part has crevice corrosion. Now the user could ask the program to justify this rule. The program could respond by giving some definitive test to perform as proof of the hypothesis. In the case, the program is actually quoting a metarule, which is knowledge about rules.

It is easy to build Explanation Facilities with rules because the antecedents of a rule specify exactly what is necessary to activate the rule. By keeping track of which rules have fired, an Explanation Facility can present the can of reasoning that led to a certain conclusion.

2.4 Production Systems

In the late 1950s and early 1960s a number of programs were written with the goal of general problem solving. The most famous of these was the General Problem Solver, created by Newell and Simon and described in a series of papers culminating in their monumental 920-page work on cognition: Human Problem Solving (Newell72).

One of the most significant results demonstrated by Newell and Simon was that much of human problem solving or cognition could be expressed by IF...THEN-type production rules. For example, IF it looks like it's going to rain THEN carry an umbrella, or IF your spouse is in a bad mood THEN don't appear happy. A rule corresponds to a small, modular collection of knowledge called a chunk. Chunks are organized in a loose arrangement with links to related chunks of knowledge. One theory is that all human memory is organized in chunks. An example of a rule representing a chunk of knowledge is

IF the car doesn't run and the fuel gauge reads empty
THEN fill the gas tank

Newell and Simon popularized the use of rules to represent human knowledge and showed how reasoning could be done with rules. Cognitive psychologists have used rules as models to explain human information processing. The basic idea is that sensory input provides stimuli to the brain. The stimuli trigger the appropriate rules of long-term memory, which produce the appropriate response. Long-term memory is where our knowledge is stored. For example, we all have rules such as

IF there is a flame THEN there is a fire
IF there is smoke THEN there may be a fire
IF there is a siren THEN there may be a fire

Notice that the last two rules are not expressed with complete certainty. The fire may be out, but there may still be smoke in the air. Likewise, a siren does not prove that there is a fire, since it may be responding to a false alarm. The stimuli of seeing flames, smelling smoke, and hearing a siren will trigger these and similar types of rules.

Long-term memory consists of many rules having the simple IF…THEN structure. In fact, as mentioned earlier, a grand master chess expert may know 50,000 or more chunks of knowledge about chess patterns. In contrast to the long-term memory, the short-term memory is used for the temporary storage of knowledge during problem solving. Although long-term memory can hold hundreds of thousands or more chunks, the capacity of working memory are surprisingly small—four to seven chunks. As a simple example of this, try visualizing some numbers in your mind. Most people can see only four to seven numbers at one time. Most people can memorize many more than four to seven numbers. However, those numbers are kept in long-term memory.

One theory proposes that short-term memory represents the number of chunks that can be simultaneously active and considers human problem solving as a spreading of these activated chunks in the mind. Eventually, a chunk may be activated with such intensity that a conscious thought is generated and you say to yourself,…."Hmm…something's burning."

The other element necessary for human problem solving is a cognitive processor. The cognitive processor tries to find the rules that will be activated by the appropriate stimuli. But not just any rule will do. For example, you wouldn't want to fill your gas tank every time you heard a siren. Only a rule that matched the stimuli would be activated. If multiple rules are activated at one time, the cognitive processor must perform a conflict resolution to decide which rule has the highest priority. That rule will be executed, for example, if both of the following rules are activated.

IF there is a fire THEN leave
IF my clothes are burning THEN put out the fire

Then the actions of one rule—with the higher priority—will be executed before the other. The inference engine of modern expert systems corresponds to the cognitive processor.

The Newell and Simon model of human problem solving in terms of long-term memory (rules), short-term memory (working memory), and a cognitive processor (inference engine) is the basis of modern rule-based expert systems. Rules like these form a Production System.

Emil Post (Post43) was the first to use production systems in symbolic logic. Post's basic idea was that any mathematical or logic system is simply a set of rules specifying how to change one string of symbols into another set of symbols. That is, given an input string, the antecedent, a production rule could produce a new string, the consequent. This idea is also valid with programs and expert systems in which the initial string of symbols is the input data and the output string is some transformation of the input.

As a very simple case, suppose the input string is "patient has fever," the output string might then be "take an aspirin." Note that there is no meaning attached to these strings. That is, the manipulation of the strings is based on syntax and not on any semantics or understanding of what fever, aspirin, and patient represent. A human knows what these strings in terms of the real world mean but a Post production system is just a way of transforming one string into another. A production rule for this example could be

Antecedent → Consequent
Person has fever → take aspirin

The arrow displayed in this rule indicates the transformation of one string. We can interpret this rule in terms of the more familiar IF....THEN notation as

IF person has fever THEN take aspirin

Although Post's production rules were useful in laying part of the foundation of expert systems, they are not adequate for writing practical programs. The basic limitation of Post's production rules in programming is lack of a control strategy to guide the application of the rules. A Post system permits the rules to be applied on the strings in any manner because there is no specification given on how the rules should be applied.

The next advance in applying production rules was made by Markov, who specified a control structure for production systems (Markov54). A Markov algorithm is an ordered group of productions that are applied in order of priority to an input string. If the highest priority rule is not applicable then the next one is applied, and so forth. The Markov algorithm terminates if either (1) the last production is not applicable to a string or (2) a production that ends with a period is applied.

Although the Markov algorithm can be used as the basis of an expert system, it is highly inefficient for systems with many rules. Efficiency is of major importance in practical systems because if the user has to wait a long time for a response, the system will not be used. What is really needed is an algorithm that knows about all the rules and can apply any rule without having to try each one sequentially. The Rete algorithm developed by Charles Forgy (Forgy82) is such a solution. It is a fast pattern matcher that obtains its speed by storing information about rules in a network. Instead of having to match facts against every rule on every recognize-act cycle, the Rete algorithm looks only for changes in matches on every cycle. This greatly speeds up the matching of facts to antecedents since the static data that don't change from cycle to cycle can be ignored. Our CES product shown in Figure 2 utilizes the Rete algorithm.

2.5 Reasoning under Uncertainty

Although there are many Expert System applications that can be done with exact reasoning, most require inexact reasoning involving uncertain facts, rules or both. Uncertainty can be considered as the lack of adequate information to make a decision. Uncertainty is a problem because it may prevent us from making the best decision or even cause a bad decision to be made.

2.5.1 Sources of Uncertainty

Sources of uncertainty include data that is ***Ambiguous***, in which something may be interpreted in more than one way, ***Incomplete***, where some information is missing, and/or ***Incorrect***, where the information is wrong, possibly due to human or equipment error. Note that incorrect data can occur with the application of a hypothesis either when a false hypothesis is accepted as true or when a correct hypothesis is rejected as false. Another source of uncertainty is the accuracy and precision errors that can occur with measurement. ***Accuracy*** is analogous to a systematic "DC" offset error from the true value. ***Precision*** contains two factors: 1) the resolution to which the item can be measured and 2) the random "AC" variation about the accuracy offset.

There can also be errors in reasoning from either ***Invalid Induction*** or ***Invalid Deduction***. An inductive argument such as "If I smell smoke then there is a fire" or "There is no fire because we never had a fire before" can never be proven true or false a priori. Inductive arguments can only provide some degree of confidence that the conclusion is correct. A deductive argument such as "My clothes are burning then there is a fire" is valid because you can see the flames. But even this argument is limited by some degree of uncertainty and it is possible to have a totally false conclusion from a deductive argument such as "If the output is normal then the valve is in good condition." The valve may be stuck in the open position and a problem would only be observed when an attempt was made to close it. Another source of uncertainty in the expert system rules is ***Heuristics*** or "rules of thumb" that are based on experience. This is because heuristics describes the expected result on the average and there can considerable variation about this mean value.

In addition to the above errors involved with the creation of individual rules, there are uncertainties associated with the assignment of probability or likelihood values to the rules as described in the next section. This uncertainty is due to the fact that these values are based on estimates from humans, so there is uncertainty in them as well. There is also an uncertainty with the likelihood of consequent and in how the multiple evidence in a given rule should be combined.

Two other sources of uncertainty that occur when the rules are combined and interact are ***Conflict Resolution*** and ***Compatibility of Rules***. The uncertainty in conflict resolution is associated with the priority assigned for firing a given rule. Compatibility of rules has uncertainty from five major causes:

1. Contradiction where the rules may fire with contradictory consequence such as "IF A THEN H" and "IF A THEN NOT(H)",

2. Subsumption where one rule is subsumed by another if a portion of its antecedent is a subset of another rule such as combining "IF A THEN H" and "IF A AND B THEN H"
3. Redundancy of rules, such as "IF A AND B THEN H" and "IF B AND A THEN H" which were accidentally entered.
4. Missing Rules where a rule is forgot or not known, and
5. Data Fusion associated with combining different types of information to from a final hypothesis, such as combining lab tests, vehicle history, climate data and subjective estimates on vehicle usage.

2.5.2 Quantifying the Uncertainty

There are a number of theories available to deal with uncertainty. We will consider using four different approaches possibly in concert with one another. These four approaches require the expert to assist in specifying one or more of four different measures of uncertainty:

- Probability Values used in classical probability theory,
- Likelihood Factors used in Bayesian probability theory,
- Certainty Factors from Confirmation theory, and
- Fuzzy Factors (or Parameters) from Fuzzy Logic.

The main purpose of this memo is to familiarize you with these different measures so you will be able to intelligently quantify the magnitude of these factors for each of the rules and facts that are used by the expert system that you will be helping to define.

Probability theory can be considered as a theory of reproducible uncertainty. It was originally developed to deal with games of chance in which the same experiment could be reproduced indefinitely. Probability theory is applied *a priori* to determine the odds in a game and *a posterior* when used in determining the probability properties of a specimen in an experimental setting. There is also a type of probability called **subjective probability** that deals with events that are not reproducible and have no historical basis on which to extrapolate, such as drilling a well at a new site. A subjective probability is actually a belief or opinion expressed as a probability. Although subjective probability is not rigorous, an estimate from an expert is better than no estimate at all and is usually very accurate (else the expert won't be an expert for long.) We will be using all three of these types of estimates of likelihood in the Corrosion Expert System.

The methods to combine probabilities when multiple events occur depend on whether the events are effect each other in any way. If they are mutually independent events then the probabilities can simply be multiplied together. Mutually independent events however are very rare. The more common situation is conditional probability $P(A|B)$ which is the probability of event A given that event B occurred. The inverse problem to determine the probability of an earlier event given that the later one occurred is solved using **Bayes' Theorem**. Another statistical method that is available for predictions in expert systems is **Markov Chains.** Markov Chains are used with temporal reasoning (i.e. events that depend on time). CORRDBMS uses the Markov

Chains method to predict the probability of transitioning from one corrosion state to another using field data.

From statistics the term hypothesis is used for some proposition whose truth or falseness is not known for sure on the basis of some evidence. The conditional probability P(H|E) then referred to as the likelihood of a hypothesis, H, based on some evidence, E. Although P(H|E) is stated as a conditional probability, it actually means something different: the likelihood or degree of belief. Probability refers to repeatable events and likelihood refers to our belief in non-repeatable events.

In order to calculate posterior odds of an event a human expert must provide two likelihood factors: ***LS = Likelihood of Sufficiency*** and ***LN = Likelihood of Necessity***. The LS factor shows how much the prior odds have changed when the evidence is present. The LN factor shows how much the prior odds are changed when the evidence is absent. Table I and II give the relationship of these likelihood factors on hypothesis and evidence.

Table I: Likelihood of Sufficiency

LS	**Effect on Hypothesis**
0	H is false when E is true or E' (no evidence) is necessary for concluding H
Small (0<LS<<1)	E is unfavorable for concluding H
1	E has no effect on belief of H
Large (1<<LS)	E is favorable for concluding H
∞	E is logically sufficient for H or Observing E means H must be true.

Table II: Likelihood of Necessity

LN	**Effect on Hypothesis**
0	H is false when E is absent or E is necessary for concluding H
Small (0<LN<<1)	Absence of E is unfavorable for concluding H
1	Absence of E has no effect on belief of H
Large (1<<LN)	Absence of E is favorable for concluding H
∞	Absence of E is logically sufficient for H

Mathematically the values of LN and LS should fall into one of three categories:

- LS > 1 and LN < 1,
- LS < 1 and LN > 1, and
- LS = LN = 1.

In practice experts do not hold to these mathematical constraints. It is not uncommon for and expert to specify an LS > 1 and LN = 1. That is, the expert is saying the observation of the evidence is important but the absence of the evidence is unimportant. If the expert specifies LS

> 1 (the evidence is in favor of the hypothesis) and LN = 1 (Lack of evidence has no impact on the hypothesis) then approximate methods such as assuming the probability is piecewise linear must be used.

In addition to having an uncertain hypothesis we often also have uncertain evidence. That is, we have partial evidence but not conclusive evidence. For example you may have the hypothesis "*IF there is oil under my kitchen THEN I'm going to get rich.*" Initially you don't know if there is oil under your kitchen. Conclusive evidence would be drilling a test well, but this is expensive. So you use partial evidence, e, to support conclusive evidence, E, such as other people in my neighborhood have struck it rich. Based on this you have high belief, perhaps P(E|e) = 98% that there is oil even though it is not conclusive. Bayesian probability then can calculate the probability that the hypothesis (you will be rich) will be true. The situation becomes more complex if there is compound evidence in the rule such as "*IF E1 AND E2 THEN H.*" This requires the expert to specify the a priori likelihoods, which they are reluctant to do. That is, what is the likelihood your house sits on top of an oil deposit before your neighbor discovered it? Is it 0.000001 or 0.0000001, or some other number? As the number of compound evidence items increase in a rule, the more complex the calculation of the probability. One simplifying solution to this problem is to use a fuzzy logic approximation for calculating the probability of all the partial evidence representing the conclusive evidence. This approximation set the probability equal to the absolute minimum probability of the partial evidence set. The main problem with this approach is that the probability P(E|e) is insensitive to any P(Ei|e) except the minimum one and if this minimum doesn't change, even if the other probabilities do change, the P(E|e) will be unchanged.

Because of the difficulties resulting from the assumption of conditional independence used to simplify Bayes Theorem, in practice it usually only useful for early prototype development of the Expert System when general behavior of the system is more important than correct numerical results. An alternative to using probabilities or likelihood factors is to ask the expert to specify normalized finite grade parameters derived from Carnap's theory of confirmation called ***Certainty Factors.*** Certainty factors were developed to overcome the major objection raise by experts to using probability theory that the sum of probabilities of "H" happening given evidence "E" and the probability that "H" won't happen (called H') must be one hundred percent.

$$P(H|E) + P(H'|E) = 1.$$

That is, an expert might confidently state that: "There is a 70% probability that you will graduate if you get an A in this course" but they did not want to say "There is a 30% chance you will NOT graduate if you get an A in the course!" There are two Certainty Factors, CHE and CHNE. **CHE** corresponds to the certainty that the hypothesis H is true give the evidence E and **CHNE** corresponds to the certainty the hypothesis is true give the evidence is absent. They both are rating scales from –1 to +1 in which –1 means "definitely not" and +1 means "definitely yes." Certainty factors are defined to be the normalized difference between believe and disbelief:

$$\begin{aligned} CHE &= (MB - MD)/(1 - \min(MB,MD)) \\ CHNE &= (MB' - MD')/(1 - \min(MB',MD')) \end{aligned}$$

Where MB or MB' is the measure of increased belief in H due to E or E' and MD or MD' is the measure of increased disbelief in H due to E or E'. Certainty factors allow an expert to express a belief without committing a value to disbelief. In fact the sum of belief and disbelief with certainty factors is zero:

$$CFE(H) + CFE(H') = 0$$

Which means that: "You are –70% certain that you will not graduate if you get an A in this course!" Certainty factors are really approximations to standard probability and have several theoretical problems that are amplified with by long inference chains or complex hypotheses.

The second approximate method is Fuzzy Logic, which was briefly introduced earlier. Fuzzy logic was originally developed for quantifying and reasoning using natural language in which words have ambiguous meanings such as "tall", "hot", "dangerous", "a little" "very much" and so on. It has been extended and applied in many fields, such as automatic camera tracking of an object, camcorders and single-lens reflex cameras. The basis of fuzzy logic is to use ***Membership Functions*** to represent evidence instead of "crisp" digital values. For example, suppose the actual response is either 0 or 1. This could graphically be represented as a step function. In fuzzy logic, the equivalent membership function would be an "S" function with some parameters specified by the expert, which are used to calculate the extent, slope and curvature of the curve. The parameters are usually given in terms of points along the curve by asking the expert to quantify thresholds for an expressed opinion. There are many different membership functions (or filters) that are used depending on the characteristic proposition and any modifiers or "hedges" that might be also be given such as "very", "slightly", "more or less", etc.

Expert Systems that use fuzzy logic or Certainty Factors are not purely probabilistic even if the Bayesian approach is taken. Whether the system is Bayesian or not, a hierarchy of terminology is used to rate the uncertainty into five general categories:

- Impossible = definitely known against,
- Possible = not definitely disproved,
- Plausible = some evidence exists,
- Probable = some evidence for,
- Certain = definitely known supporting.

It is likely that the final Corrosion Expert System CES will used all four methods of quantifying uncertainty depending on the rule or fact being described.

2.6 Language Shells and Tools

The Corrosion Expert System (CES) is programmed in its own special "higher-order" language provided by Jess (Java Expert System Shell). An expert system language is a higher-order language than languages like Java, LISP or C because it is easier to do certain things such as pattern recognition, but there is also a smaller range of problems that can be addressed. That is, the specialized nature of expert system languages makes them suitable for writing expert systems but not for general-purpose programming. In many situations, it is even necessary to exit temporarily from an expert system language to perform a function in a procedural language.

The primary functional difference between expert system languages and procedural languages is the focus of representation. Procedural languages focus on providing flexible and robust techniques to represent data. For example, data structures such as arrays, records, linked lists, stacks, queues, and trees are easily created and manipulated. Modern languages such as Java and Ada are designed to aid in data abstraction by providing structures for encapsulation such as modules and packages. This provides a level of abstraction that is then implemented by methods such as operators and control statements to yield a program. The data and methods to manipulate it are tightly interwoven. In contrast, expert system languages focus on providing flexible and robust ways to represent knowledge. The expert system paradigm allows two levels of abstraction: data abstraction and knowledge abstraction. Expert system languages specifically separate the data from the methods of manipulating the data. An example of this separation is that of facts (data abstraction) and rules (knowledge abstraction) in a rule-based expert system language.

Because of their sequential nature and serious limitation in manipulating symbols imperative languages are not very efficient for directly implementing expert systems, especially rule based ones. For example, the XCON system used by DEC to configure computer systems has about 7000 rules in its knowledge base. The direct way of coding this knowledge in an imperative language would require 7000 IF…THEN statements or a very long CASE. This style of coding would present major efficiency problems since all 7000 rules need to be searched for matching patterns on every recognized-act cycle. The XCON expert system accomplishes this in one step.

2.7 Elements of an Expert System

The elements of the CES expert system are shown in Figure 1. In a rule-based system the knowledge base contains the domain knowledge needed to solve problems coded in the form of rules. An expert system consists of the following components:

- User interface – the mechanism by which the user and the expert system communicate.
- Explanation facility—explains the reasoning of the system to a user.
- Working memory—a global database of facts used by the rules.
- Inference engine—makes inferences by deciding which rules are satisfied by facts or objects, prioritizes the satisfied rules, and executes the rule with the highest priority.
- Agenda—a prioritized list of rules created by the inference engine, whose patterns are satisfied by facts or objects in working memory.
- Knowledge acquisition facility—an automatic way for the user to enter knowledge in the system instead of having the knowledge engineer explicitly code the knowledge.

The knowledge acquisition facility is an important feature in CES and is found on only the most sophisticated expert systems. In some expert system tools like KEE and First Class the tool can learn by rule induction through examples and can automatically generate rules. However, the examples are generally from tabular or spreadsheet-type data better suited to decision trees. General rules constructed by a knowledge engineer can be much more complex than the simple rules from rule induction.

The user interface for CES will be a Graphical User Interface (GUI) familiar to most Windows, Mac and Internet users. This capability will be provided as a Java application.

The knowledge base is also called the production memory in a rule-based expert system. As a simple example, consider the problem of deciding to cross a street. The productions for the two rules are as follows, where the arrows mean that the system will perform the actions on the right of the arrow if the conditions on the left are true.

The light is red → stop
The light is green → go

The production rules can be expressed in an equivalent pseudo-code IF....THEN

Rule: Red_light
IF
the light is red
THEN
stop

Rule: Green_light
IF
the light is green
THEN
go

Each rule is identified by a name, followed by the IF part of the rule. The section between the IF and THEN parts of the rule is called by various names including the antecedent, conditional part, pattern part, or left-hand-side (LHS). The individual condition: "*the light is green*" is called a conditional element or a pattern

For example the actual rules from the MYCIN system for diagnosis of meningitis and bacteremia (bacterial infection) are:

IF
The site of the culture is blood, and
The identity of the organism is not known with certainty, and
The stain of the organism is gramneg, and
The morphology of the organism is rod, and

The patient has been seriously burned

THEN

There is weakly suggestive evidence (.4) that the identity of the organism is pseudomonas.

2.8 Relationship with Future Research or Research and Development

CES's unique Knowledge Acquisition Facility will allow user companies and agencies to continue to build the knowledge base. This will result in three significant advantages for the future. First the Expert System will continue to grow and learn becoming more useful and intelligent over time. Second, the facility will allow companies to incorporate proprietary design information and data to tailor the system to their needs without fear of exposing this information to others. This capability will make the system more marketable to industry. Third, it will allow the input of deterioration data for other materials and causes then originally included in the Phase II final product. It is expected that many new uses of the system will be discovered by this means.

It is anticipated that the Vehicle Corrosion Expert System resulting from this effort will be used to evaluate corrosion control materials, treatments, and processes for use on any vehicle system. This will allow users to evaluate new materials with significantly less effort than was previously possible. The most common areas for using the model would probably be in system design. The Expert System would allow users with little knowledge about corrosion to evaluate the potential for various corrosion modes to occur in service. Based on the data output from the Expert System model, the need for expensive corrosion testing may be minimized or eliminated.

The model may also be useful during R&D of new materials. Concerns over the environmental and work health impacts of many materials commonly used for corrosion control (e.g., lead, cadmium, chromium) has spawned a number of R&D efforts investigating alternatives to these materials. The Expert System contemplated by this research effort will be an effective tool in evaluating alternative corrosion control technologies.

3.0 Conclusions from the Phase I effort and Recommendations for Phase II

One of the most significant conclusions formulated during the Phase I effort was that the development of an expert system to forecast corrosion and deterioration of an automotive system is a very large and challenging project. There is a need to focus on a few important areas in order to make the final Phase I product significant and useful to the Government and industry (and therefore the Phase III commercialization viable). A series of meetings and discussions were held with experts from the Army, General Motors, Ford, Daimler Chrysler, American Iron and Steel Institute, International Magnesium Association, the Aluminum Association and National Center for Manufacturing Sciences. It was concluded from these meetings that the most significant challenge to help the automotive industry was a system that would concentrate on uniform and galvanic corrosion and how they may be influenced by and interact with poultice and crevice corrosion.

Indeed, the number one concern among automotive manufactures for their future designs is the high probability of galvanic corrosion of new lightweight aluminum and magnesium components. As shown in Figure 6, magnesium is anodic (or sacrificial) to all other engineering metals and has a propensity for uniform corrosion as well. Future automobiles and trucks will have a significant amount of these materials in the engine compartment, frames and chassis. Although the vehicles are being designed to insolate any coupling of metals with a high galvanic corrosion potential, it is anticipated that the problem will be difficult to avoid during operation, particularly when combined with other forms of corrosion such as crevice and poultice corrosion.

Polarization curves and the mixed potential can be used to determine the magnitude of increased corrosion rate on the more active metal, and the reduction in corrosion rate of the more noble metal. However, there are so many factors that affect the corrosion rates (such as crevices, and crevice geometry) that it is a difficult task. In addition to the magnitude of the galvanic effect, knowing which metal is the more noble in a galvanic couple is very important. The expert system therefore should give advice as to the proper design and operation selections.

The overall goal of the Phase I effort is to develop a robust expert system to assist the vehicle designers, corrosion testing groups, maintenance personnel, and logistics managers in anticipating the deterioration of the vehicle as a result of design decisions and environment vehicle use scenarios.

To achieve this goal, the expert system must be developed with the following software specific functional objectives:

- Identify and prioritize knowledge sources,
- Develop knowledge acquisition software system for populating the CES knowledge base,
- Create an inference engine
- Populate the knowledge base with expert rules on uniform, galvanic, poultice and crevice corrosion,
- Design a detailed control structure for processing the rules,

- Develop a friendly intuitive user interface,
- Develop a detailed users manual for the system,
- Develop an Explanation Facility to provide the user with logic used by the expert system to arrive at a conclusion,
- Write detailed implement specification documentation for each software element.
- Develop a test plan for validating the system,
- Document installation/operation of the system,
- Code, test and debug the software,
- Analyze and document test results and,
- Write a system level report at the conclusion of each software development life cycle.

Our corrosion application specific goals are to:

- Assemble detailed databases on galvanic corrosion of metals
- Develop a methodology to predict galvanic corrosion (mass loss) as function of:
  - Effective Area Ratio
  - Time of Wetness
  - Chemical composition of any build up on the metal's surface
  - Initial thickness of protected layer when a galvanic couple is established
- Assemble a "Lessons Learned" design database for avoiding uniform, galvanic, crevice, and poultice forms of corrosion
- Develop a methodology for predicting mass loss from crevice corrosion
- Develop a methodology for predicting mass loss from poultice corrosion
- Develop a methodology for predicting stress cracking of metals and plastics
- Develop a methodology for predicting the deterioration of rubbers and plastics
- Develop a methodology for predicting the deterioration of composite materials.

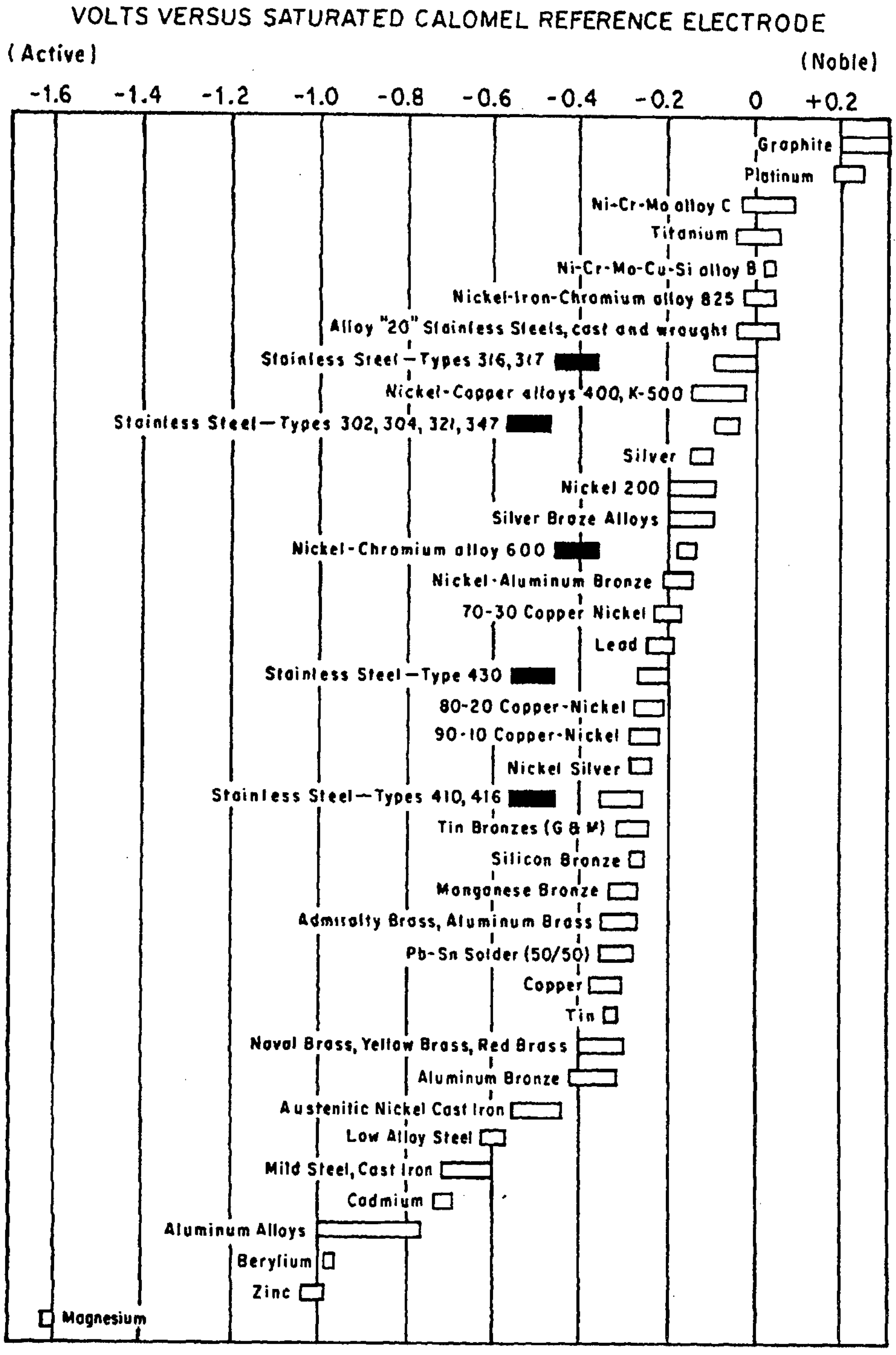


Figure 6: Galvanic Series of Metals

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Appendix A: Logic Tree for Expert System Demo

Component Materials – Question 1

Are the materials on the galvanic series?
Yes → Go to question 2.
No → User input required.
Are these metals?
Yes → Are they the same metals?
Yes → No galvanic corrosion problem. End.
No → Galvanic corrosion possible, need more information or testing. Go to question 1.
No → Are they conductive?
Yes → Is one a metal
Yes → Galvanic corrosion possible, need more information or testing. Display: "Galvanic corrosion may be possible. Need additional information or testing to confirm this. Consider redesign on component or alternative materials. Note, no environmental, area ratio or corrosion data has been used to determine galvanic corrosion." End
No → No galvanic corrosion problem. End.
No → No galvanic corrosion problem. End.
I don't know → Need more information or Perform testing. Assume that components are not conductive. Display: "Galvanic corrosion likely not possible assuming components are non metallic and non-conductive. Recommend performing additional testing or gathering additional information to confirm this." End.
I don't know → Need more information. Display: "Galvanic corrosion may be possible if the materials are metals. If materials are not metals galvanic corrosion may not be possible. Need additional information before proceeding." End.
I don't know → Assume metals are significantly apart on the galvanic series, allowing galvanic corrosion. Display caveat (also display at end): "Materials assumed to be metals significantly apart on the galvanic series, thus increasing the likelihood of galvanic corrosion. This will be used to estimate likelihood of galvanic corrosion." Go to question 2.

Component Materials – Question 2

Are these the same metal?
Yes → Are they the same alloy?
Yes → No galvanic corrosion problem. End.
No → Lookup metals on galvanic series. → Go to question 3.
I don't know → Need more information. Assume they are not the same alloy. Display caveat (also display at end): "Metals assumed to be different alloys, thus allowing galvanic corrosion. Need to perform additional testing or research to confirm this." Go to question 3.
No → Lookup metals on galvanic series. → Go to question 3.
I don't know → Need more information. Assume they are not the same metal. Display caveat (also display at end): "Metals assumed to be different, thus allowing galvanic corrosion. Need to perform additional testing or research to confirm this." Go to question 3.

Component Materials – Question 3

What are the surface areas on the metals?
User Input
Is anodic material larger than cathodic material?
Yes → Galvanic corrosion potentially less severe. → Go to question 4.
No → Galvanic corrosion potentially more severe. → Go to question 4.
I don't know → Need more information. Assume areas are the same. Display caveat (also display at end): "Metals assumed to be the same area. An increase in the area of the more cathodic (less active metal) will potentially result in more severe galvanic corrosion. Need additional information." Go to question 4.

Component Structure – Question 4

Is there electrical contact between the metals?
Yes → Is this electrical contact necessary for component function?
Yes → Go to question 6.
No → Can an insulator be used to isolate these materials?
Yes → Go to question 5.
No → Go to question 6.
I don't know → Need more information. Assume electrical contact necessary for component function. Display caveat (also display at the end): "Direct metal contact assumed to be necessary for component function. Direct electrical contact will allow galvanic corrosion to occur. Drawings and specifications should be reviewed to confirm this." Go to question 5.
No → User input required.

Is there an insulator other than air?

Yes → Go to question 5.

No → No galvanic corrosion problem. End.

I don't know → User input required.

Are metals physically touching?

Yes → Electrical contact = Yes. Go to question 4 with "Yes" response.

No → Are they joined by welding, bolt, rivet, other mechanical joint?

Yes → Electrical contact = Yes. Go to question 4 with "Yes" response.

No → Electrical contact Go to question 4.

With "No" response

I don't know → Need more information. Assume that metals are physically touching. Display caveat (also display at the end): "Metals are assumed to be physically touching. This contact will allow galvanic corrosion to occur. This should be confirmed by reviewing drawings and specifications." Go to question 5.

Component Structure – Question 5

What is the insulator or coating material?

User Input

Will wear of the insulator occur?

Yes → Is this a high resistance insulator?

Yes → Will the insulator last for the component service life?

Yes → No galvanic corrosion problem. End.

No → Can another insulator material be substituted?

Yes → Consider other insulator materials. Display: "Other insulator materials are available for this component. Consider materials that may have a higher resistance. A higher resistance will help prevent galvanic corrosion. Repeat question 5 with higher resistance material (if no alternative material has a higher resistance repeat with original material)." Go to question 5.

No → Electrical contact may eventually occur. Go to question 6.

I don't know → Consider other insulator materials or Perform testing. Assume insulator will last for the service life of the component. Display caveat (also display at the end): "Insulator material is assumed to last for the service life of the component being evaluated. The existence of a high resistance insulator between dissimilar metals will prevent galvanic corrosion. No galvanic corrosion problem." End.

No → Can another insulator be used?

Yes → Consider other insulator materials. Display: "Other insulator materials are available for this component. Consider materials that may have a higher resistance. A higher resistance will help prevent galvanic corrosion. Repeat question 5 with higher resistance material (if no alternative material has a higher resistance repeat with original material)." Go to question 5.

No → Electrical contact may occur. Go to question 6.

I don't know → Consider other insulator material or Perform testing. Assume that insulator material is optimal for this design. Display caveat (also display at end): "Insulator material is assumed to be ideal for the intended use. Electrical contact may occur due to wear of this insulator. Other insulator materials should be researched and tested. If an alternative material is found, re-run program substituting it for the selected material." Go to question 6.

No → Is this a high resistance insulator?

Yes → No galvanic corrosion problem. End.

No → Can another insulator be used?

Yes → Consider other insulator materials. Go to question 5.

No → Electrical contact may eventually occur. Go to question 6.

I don't know → Need additional information. Assume another insulator can not be used. Display caveat (also display at the end): "Insulator is assumed to be the ideal material for this design. Since this is not a high resistance insulator, galvanic current may be passed through it, thus allowing galvanic corrosion to take place. However, corrosion may occur at a slower rate. Research or test other materials for substitution, which are higher resistance for this application. Re-run program when additional materials are discovered." Go to question 6.

I don't know → Need additional information or Perform testing. Assume insulator is a high resistance insulator. Display caveat (also display at end): "Insulator being considered is assumed to be a high resistance insulator. Since this insulator will not experience wear during service, it should prevent galvanic corrosion. Research or testing should be performed to confirm that this is a high resistance insulator. If found to not be such, the program should be re-run." End.

I don't know → Can another insulator be used?

Yes → Consider other insulator materials or Perform testing. Go to question 5.

No → Go to question 6.

I don't know → Need additional information. Assume insulator is the ideal material for this component and wear will not occur. Display caveat (also display at end): "This insulator material assumed to be ideal for this component. No wear of the insulator material was assumed to be able to occur. If this is a high resistance insulator no galvanic corrosion will occur. If this is not a high resistance insulator, galvanic corrosion may be possible. Component structure will be re-evaluated using these assumption." Go to question 5 with these assumptions.

Component Structure – Question 6

Is this the optimal design for this component?

Yes → Go to question 7.

No → Is this design necessary for function of this vehicle?

Yes → Go to question 7.

No → Suggest alternative designs. Go to question 6.

I don't know → Need more information on component. Assume design is necessary for function of vehicle. Display caveat (also display at end): "Component design is assumed to be necessary for function of the vehicle. Alternative designs may be considered that more closely matches the optimal design for this component. Additional research or testing should be performed to determine is alternative designs are feasible. If they are, the program should be re-run." Go to question 7..

I don't know → User input required → Were alternative designs considered?

Yes → Are they more corrosion resistant?

Yes → Is other design possible for use?

Yes → Suggest replacing with other design.

No → Go to question 7.

No → Go to question 7.

I don't know → Need additional information or Perform testing. Assume alternative designs are less corrosion resistant. Display caveat (also display at end): "Alternative designs are assumed to be less corrosion resistant. Additional research or testing is recommended to confirm this. If found to be more corrosion resistant, re-run program substituting these designs for the original. Go to question 7.

No → Are other designs available?

Yes → Provide additional information on alternative designs.

No → Go to question 7.

I don't know → Need more information on component. Assume other designs are not available. Display caveat (also display at end): "Assumed alternative designs are not available. Additional research and testing is recommended to confirm this. If alternative designs can be used, re-run program to see if these would help minimize galvanic corrosion." Got to question 7.

I don't know → Need more information on component design. Assume other designs are not available. Display caveat (also display at end): "Assumed alternative designs are not available. Additional research and testing is recommended to confirm this. If alternative designs can be used, re-run program to see if these would help minimize galvanic corrosion." Got to question 7Go to question 6.

Operating Environment – Question 7

Will the metals come in contact with an electrolyte?

Yes → Is this a low resistivity electrolyte?

Yes → What is the estimated percent time in contact? User input. → Go to question 8.

No → What is the estimated percent time in contact? User input. → Go to question 8.

I don't know → Need more information. Assume component will not come into contact with electrolyte. Display caveat (also display at end): "Component assumed not to come into contact with an electrolyte. An electrolyte is necessary for galvanic corrosion. Recommend perform additional research or testing to confirm this. Galvanic corrosion assumed not to be a problem." End.

No → No galvanic corrosion problem. End.

I don't know → Is there a crevice between the metals that will trap moisture or poultice?

Yes → Is the installation area readily open to outside contaminants?

Yes → Electrolyte contact = Yes. Go to question 7 with "Yes" response.

No → User input required. → Has moisture, poultice or other contaminants been found in the area on previous designs?

Yes → Electrolyte contact = Yes. Go to question 7 with "Yes" response.

No → Electrolyte contact = No. → No galvanic corrosion problem. End.

I don't know → Need more information or perform testing. Assume component will not come into contact with electrolyte. Display caveat (also display at end): "Component assumed not to come into contact with an electrolyte. An electrolyte is necessary for galvanic corrosion. Recommended performing additional research or testing to confirm this. Galvanic corrosion assumed not to be a problem." End.

I don't know → Need more information or perform testing. Assume installation is not readily accessible by outside components. Display caveat (also display at end): "Installation assumed to completely protect component from outside contaminants. Recommend that additional research or testing be performed to confirm this. Galvanic corrosion should not be a problem if no outside contaminants can reach crevice areas." End.

No → Is there a potential for water, poultice or other contaminants to build-up on component surface and contacting both metals?

Yes → Electrolyte contact = Yes. Go to question 7 with "Yes" response.

No → Electrolyte contact = No. → No galvanic corrosion problem. End.

I don't know → Need more information or perform testing. Assume water, poultice or other contaminant cannot collect on component surface. Display caveat (also display at end): "Collection of water, poultice or other contaminants and electrolytes assumed to not be possible. Recommend that additional research or testing is performed to confirm this. Absence of an electrolyte will prevent galvanic corrosion." End.

I don't know → Need more information or perform testing. Assume that no crevice exists on the component. Display: "Assumed that no crevice exists on this component. Operating environment condition questions will be repeated using this assumption." Repeat question 7 with crevice question = NO.

Operating Environment – Question 8

Will the component be immersed in natural waters?

Yes → Is this a low resistivity electrolyte?

Yes → User input. → Percent of time exposed to natural waters.

No → User input. → Percent of time exposed to natural waters.

I don't know → Need more information or perform testing. Assume electrolyte is a low resistivity electrolyte. Display caveat (also display at end): "Resistivity of bodies of water assumed to be low." Repeat question 8 with electrolyte assumed to be low resistivity for natural waters.

No → See above to determine if galvanic corrosion is possible and display results of analysis and all caveats. End.

I don't know → Will the vehicle experience fording events?

Yes → Is the component located below the fording level?

Yes → Immersion in natural waters = Yes. Go to question 8 with "Yes" response.

No → End.

I don't know → Need more information. Assume component not located beneath the fording level. Display caveat (also display at end): "Component assumed to not be beneath the fording level of the vehicle. Galvanic corrosion may still be possible based on other analyses. Recommend perform additional research or testing to confirm whether or not fording events will occur." See above to determine if galvanic corrosion is possible and display results of analysis and caveats. End.

No → Will any other immersion event occur?

Yes → Is the component located in an area that will be immersed?

Yes → Immersion in natural waters = Yes. Go to question 8 with "Yes" response.

No → See above to determine if galvanic corrosion is possible and display results of analysis and all caveats. End.

I don't know → Need more information. Assume other immersion event will not occur. Display caveat (also display at end): "Assumed no immersion of the vehicle will occur. Galvanic corrosion may still be possible based on other analyses. Recommend perform additional research or testing to confirm the absence of immersion events." See above to determine if galvanic corrosion is possible and display results of analysis and all caveats.

No → See above to determine if galvanic corrosion is possible and display results of analysis and all caveats. End.

I don't know → Will vehicle be used in or around natural waters?

Yes → Immersion in natural waters = Yes. Go to question 8 with "Yes" response.

No → See above to determine if galvanic corrosion is possible and display results of analysis and all caveats. End.

I don't know → Need more information. Assume vehicle will not be used in or around natural waters. Display caveat (also display at end): "Assumed vehicle will not be used in or around bodies of water. Galvanic corrosion may be possible by other analyses. Recommend perform additional research or testing to confirm vehicle will not be used around these water." See above to determine if galvanic corrosion is possible and display results of analysis and all caveats.

I don't know → Need more information. Assume vehicle will not experience fording events. Display caveat (also display at end): "Assumed no fording event will occur. Galvanic corrosion may be possible by other analyses. Recommend perform additional research or testing to confirm that fording events will not occur." See above to determine if galvanic corrosion is possible and display results of analysis and all caveats.

Analysis Section

Display results of analysis of galvanic corrosion on the component evaluated.

Display all user information here.

Display all assumptions here.

Display all caveats here.